Stay Fresh: Speculative Synchronization for Fast Distributed Machine Learning

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Outline

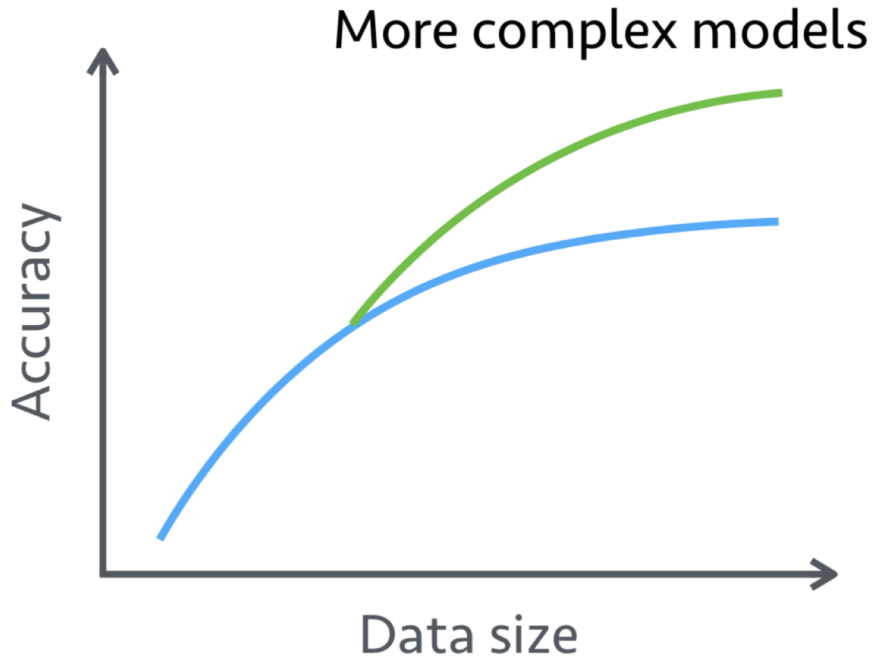
- Background and Motivation
- Insights of Distributed Asynchronous Learning
- Solution: Speculative Synchronization
- Implementation
- Evaluation
- Conclusion

Large Scale Machine Learning

- Machine learning learns from data
- More data leads to better accuracy
- Complex models can further improve accuracy

Big data and complex models

Distribute workload among many machines



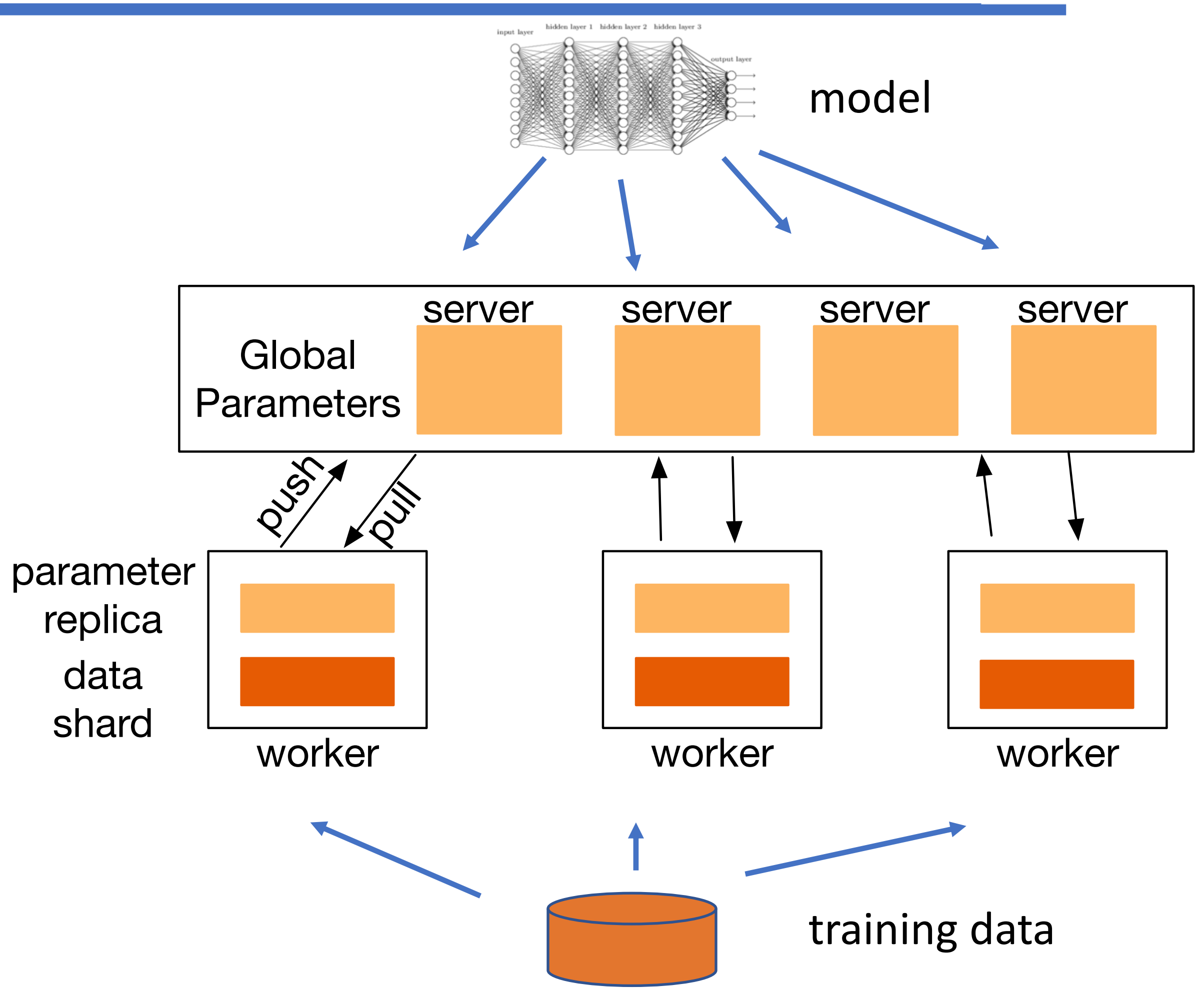
[1] Li, Mu. "Scaling distributed machine learning with system and algorithm co-design." Diss. Intel, 2017.

Parameter Server

state-of-the-art architecture for distributed ML

Iterate until stop:

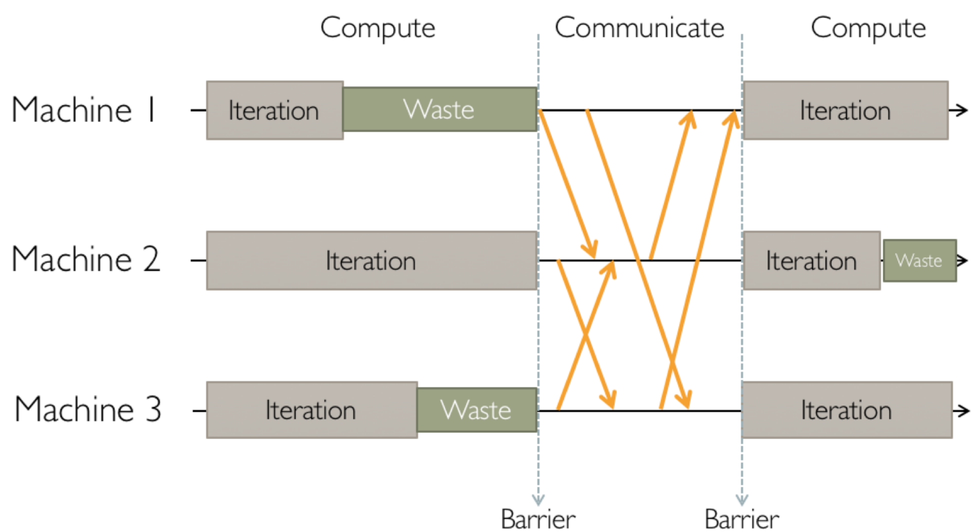
- workers compute updates
- workers ***push*** updates
- servers update model
- workers ***pull*** updated model



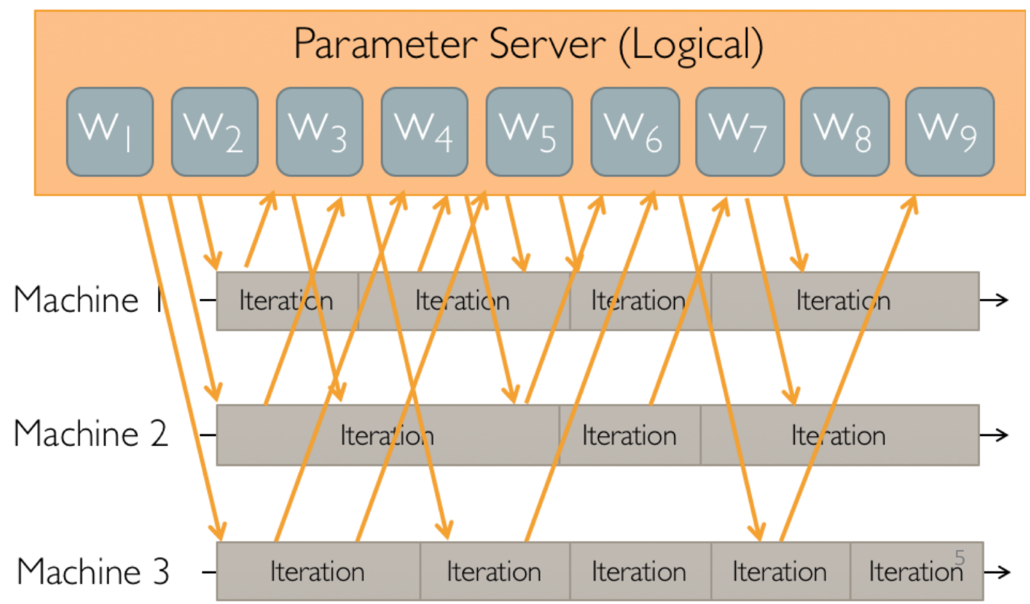
[1] Li, Mu, et al. "Scaling Distributed Machine Learning with the Parameter Server." OSDI. Vol. 14. 2014.

Synchronization Schemes

- Bulk Synchronous Parallel (BSP)
  - Strong consistency
  - Straggler
  - Concurrent communication
  - Low throughput



- Asynchronous Parallel (ASP)
  - No barrier
  - High throughput
  - Cheap synchronization
  - Inconsistency



Inconsistency and Convergence

- Inconsistent model replicas among workers
- Stale parameters poison convergence
- Stale Synchronous Parallel (SSP) : bound the staleness

Parameter replica:
the fresher the better

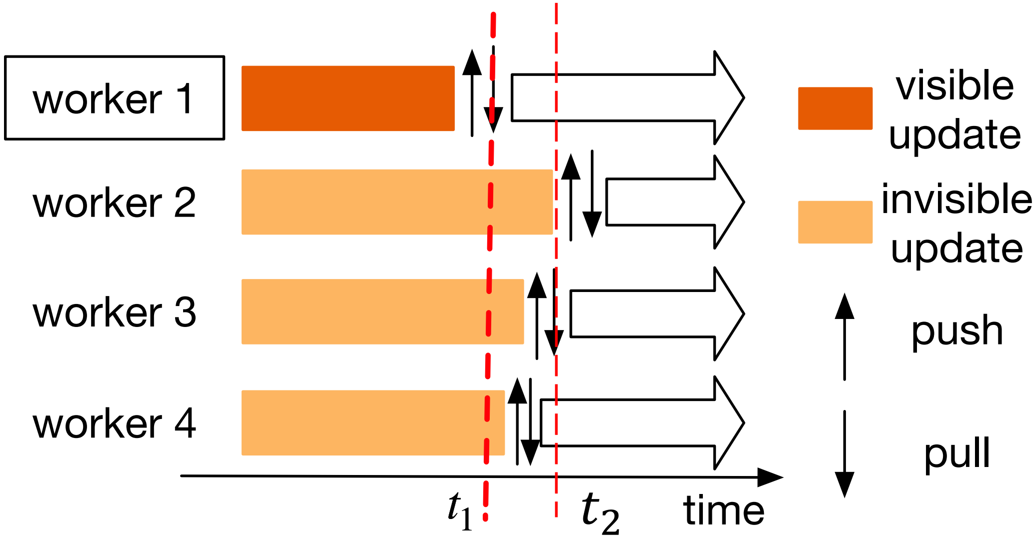
- tradeoff between update rates and update quality

Asynchronous learning → Higher rate of updates — Good for convergence

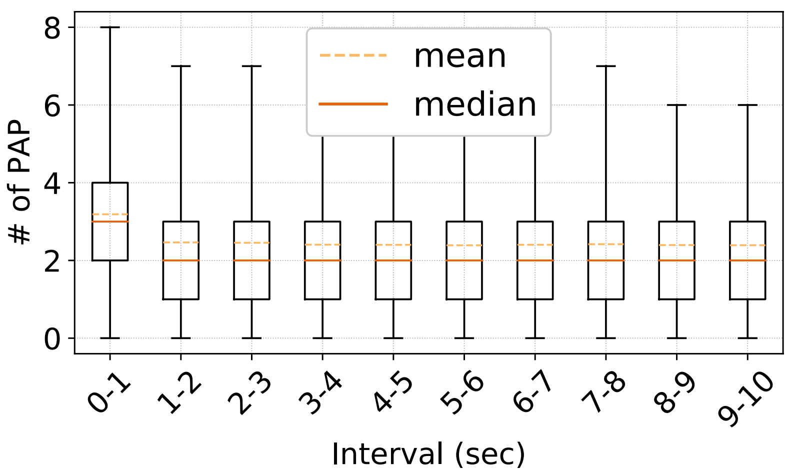
Asynchronous learning → Lower quality of updates — Bad for convergence

[1] J. Langford, A. J. Smola, and M. Zinkevich, “Slow learners are fast,” in NIPS, 2009.

Insights: Pushes after Pull

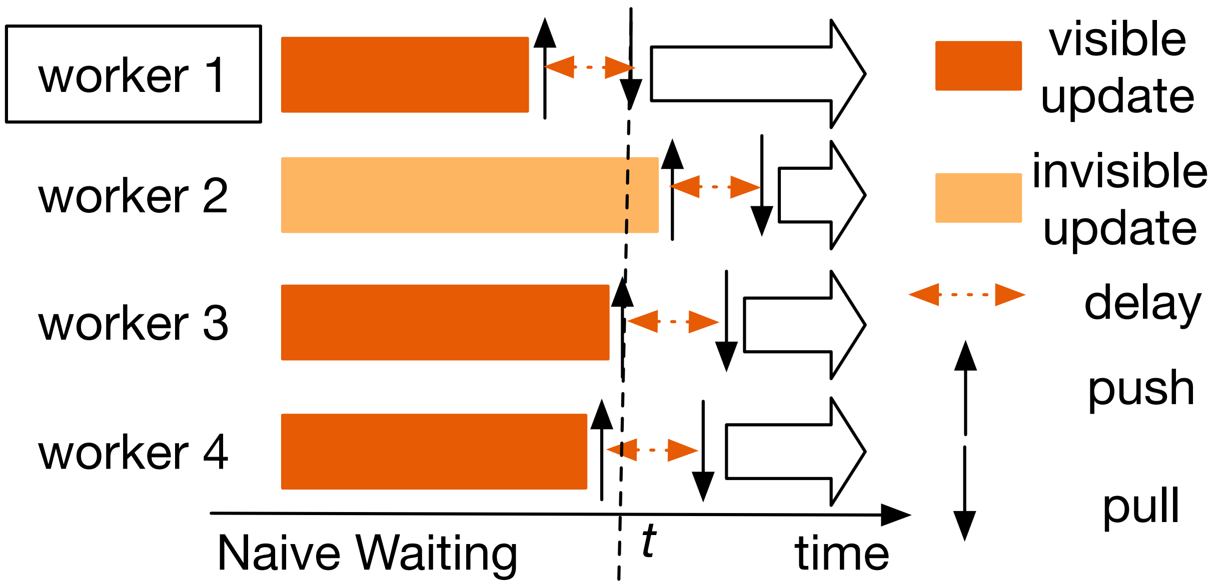


- Worker 1 eagerly pulls after push
- Misses updates from others



- 3 PAPs on average
- Missed opportunity for fresher parameters

Naïve Waiting

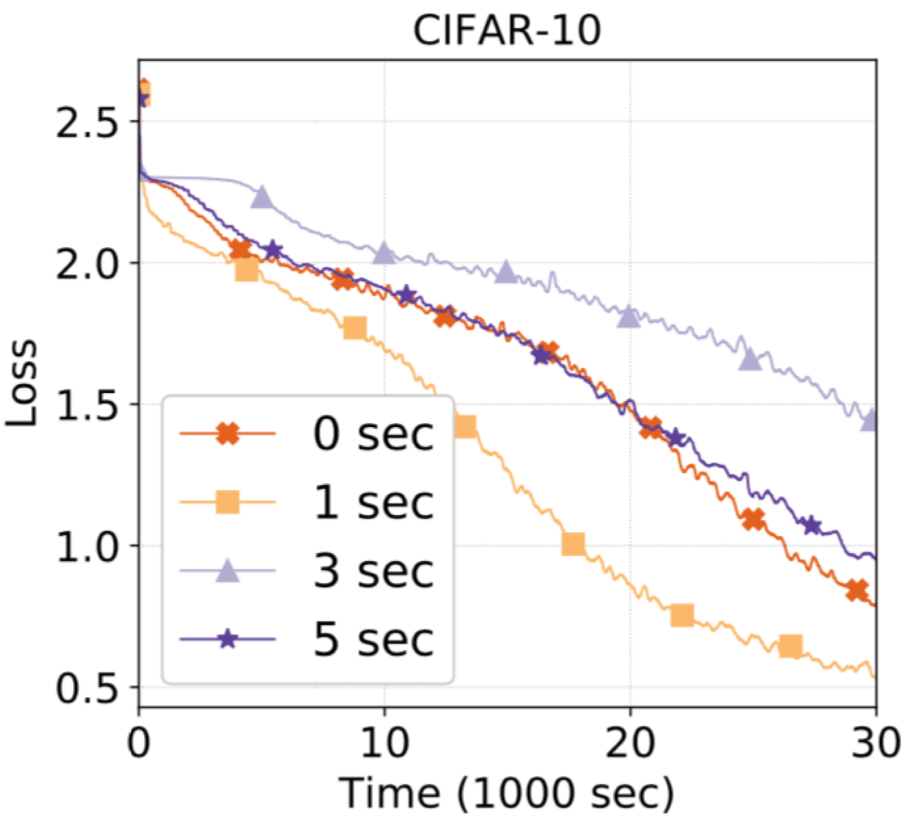


Intuition

simply *defer* the pull request

PAPs will be included

Naïve Waiting



- Works, but not always

Desired:

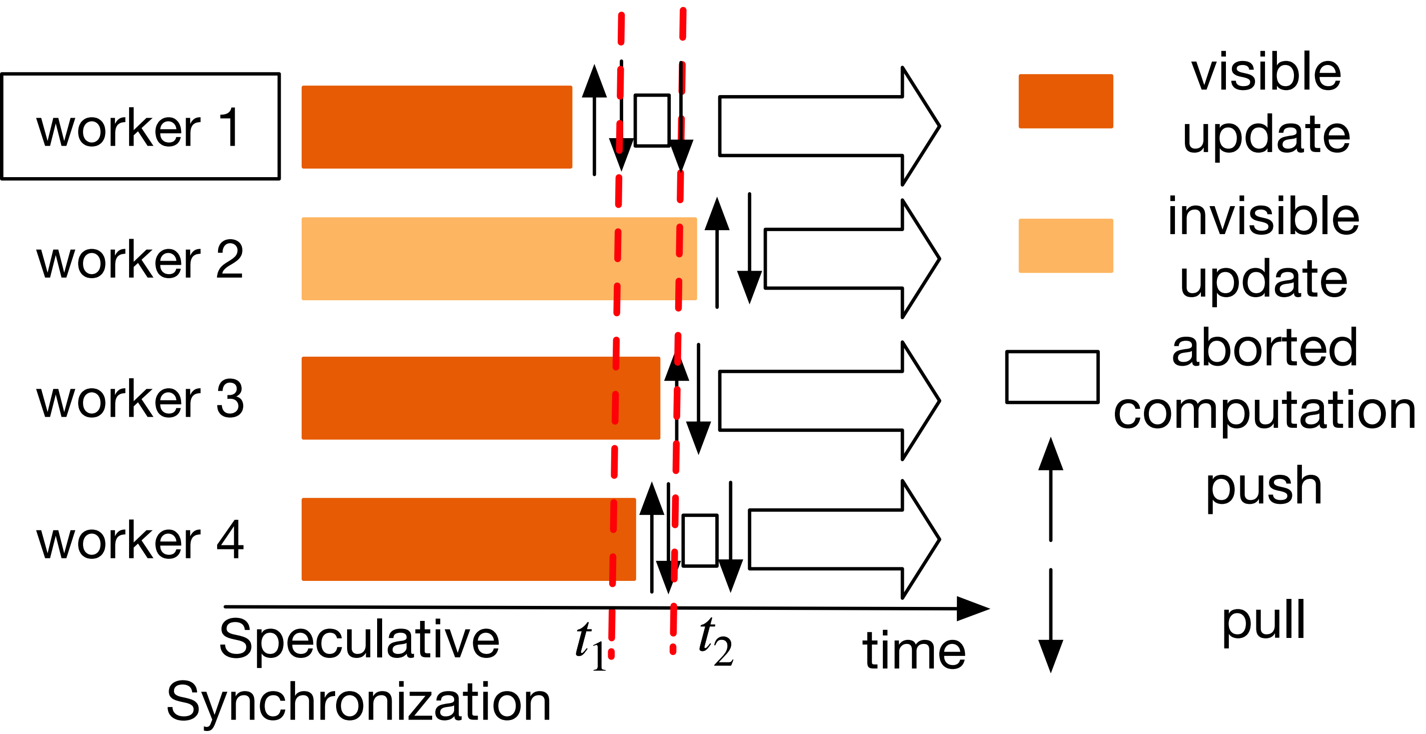
freshness gain > computation loss

Invalid wait:

freshness gain < computation loss

Speculative Synchronization

SpecSync: speculatively abort the ongoing computation and start over with fresher parameters



Gain:
fresh parameters

Lost:
aborted computation

Speculative Synchronization

Advantages:

- Avoid invalid waits
- Minimize the cost of wasted computing cycles
- Suitable for asynchronous models including ASP and SSP

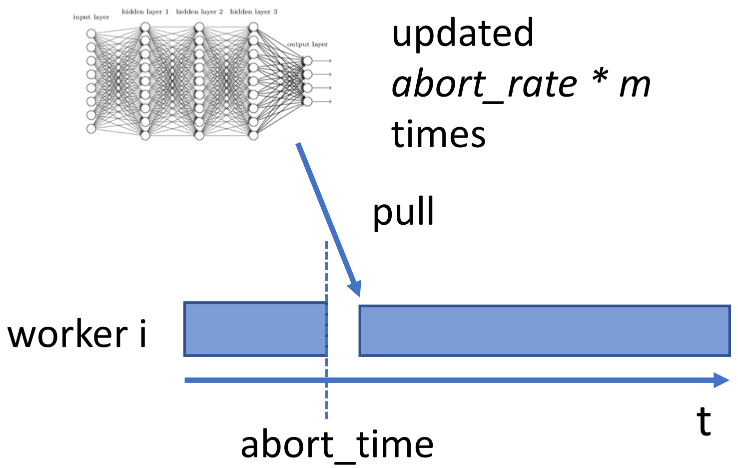
Challenges:

- Efficient communication
  - Exchange worker progress
  - Additional parameter pull
- When to abort and restart

Hyperparameters

abort_time and abort_rate

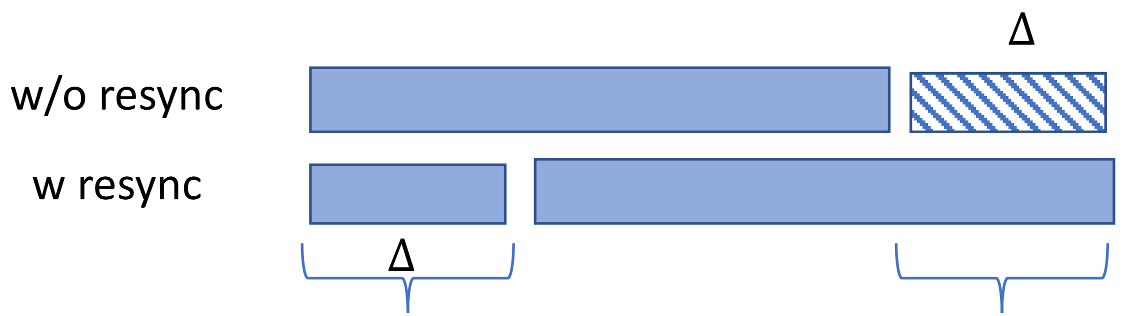
For a worker, in the first *abort_time*, if more than *abort_rate * m* updates arrive at severs, re-synchronize.



Given a workload, how do we choose abort_time and abort_rate?

Formulation

How to model the gain and loss of re-synchronization?



Gain:
More updates from other workers

Loss:
Other worker lose 1 update from the delay

net gain = *uncovered updates* - *missed peers*

$$F_{i,\tau}(\Delta) = u_{i,\tau}(\Delta) - l_{i,\tau}(\Delta)$$

Only re-sync when $F_{i,\tau}(\Delta) > 0$

Formulation

Sum up the gain over all workers in epoch τ

$$maximize_{\Delta} F_{\tau}(\Delta) = \sum_{i=1}^{m} (u_{i,\tau}(\Delta) - l_{i,\tau}(\Delta))$$

How to solve?

- Direct solution: require exact push/pull sequence ❌
- Estimation: use traces and expectations from last epoch

Adaptive Tuning

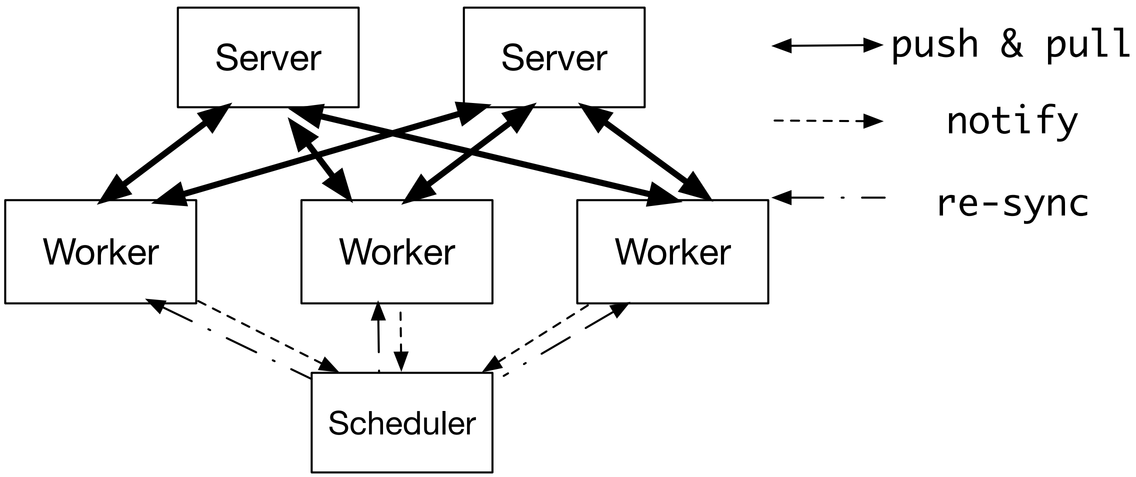
Once we have optimal Δ^*

- Set *abort_time* to Δ^* to maximize potential gain
- Set *abort_rate* to the expected missed peers
- Only abort if the gain outweighs loss

Implementation

An extension to MXNet.

Centralized design



Scheduler:

- Keep tracks of updates
- Tune abort_time and abort_rate
- Issue re-sync command to workers

Evaluation

- Effectiveness
  - Accuracy and runtime
- Robustness
  - heterogeneity and scalability
- Communication Overhead

Evaluation Setup

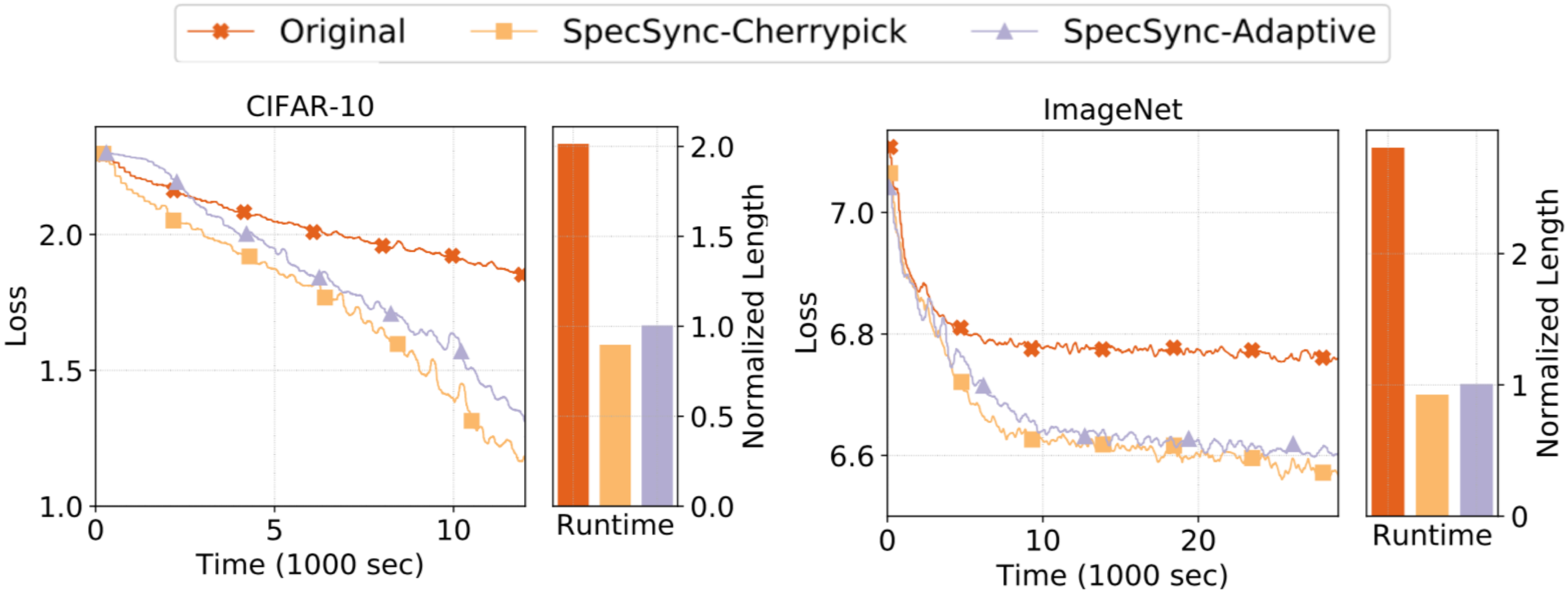
- Workload

workload	# parameters	dataset	dataset size
MF	4.2 million	Movielens	100,000
CIFAR-10	2.5 million	CIFAR-10	50,000
ImageNet	5.9 million	ImageNet	281,167

- Schemes
  - Original: stock MXNet asynchronous implementation
  - SpecSync-*cherrypick*: SpecSync with cherrypicked hyperparameters
  - SpecSync-*adaptive*: SpecSync with adaptively tuned hyperparameters
- Testbed
  - AWS EC2

Effectiveness

40 m4.xlarge instances

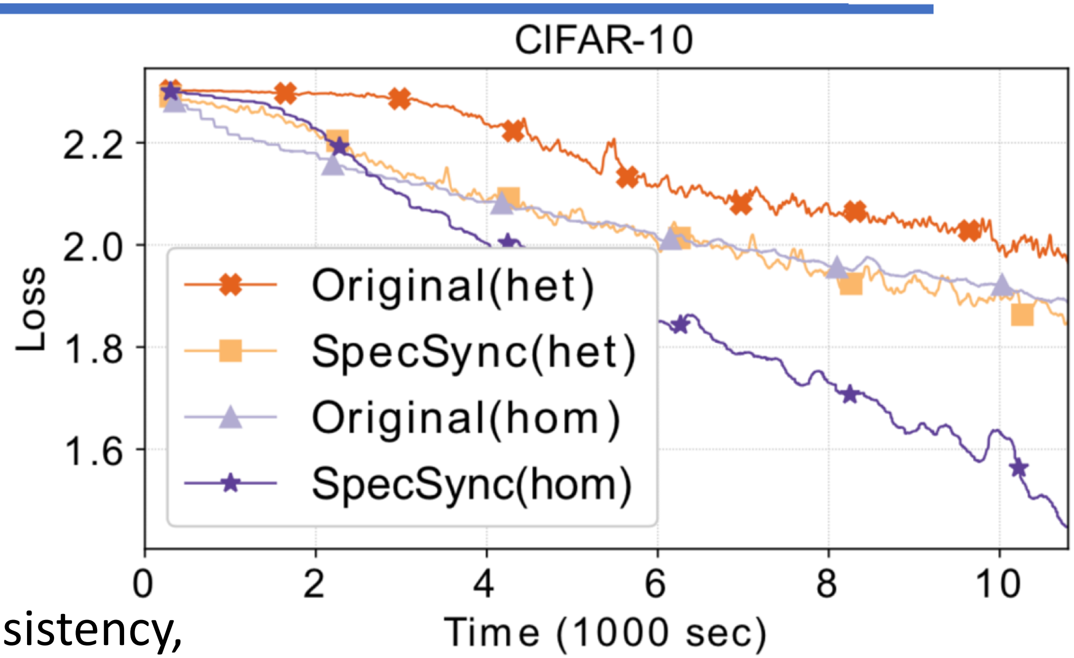


- SpecSync improves performance
- 2.97× 2.25× 3× speedup respectively
- Adaptive tuning, comparable speedups

Robustness

- Heterogeneity

10 m3.xlarge+ 10 m3.2xlarge +
10 m4.xlarge + 10 m4.2xlarge

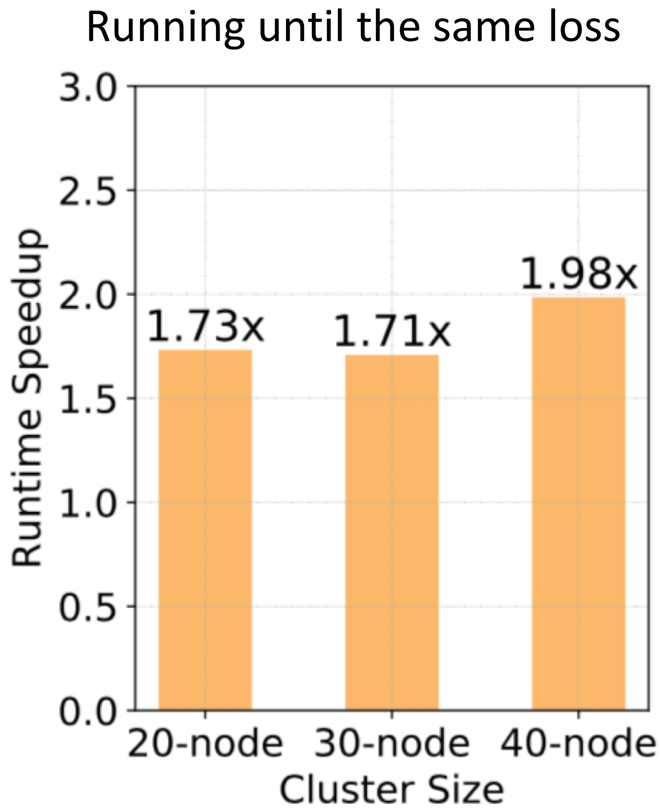


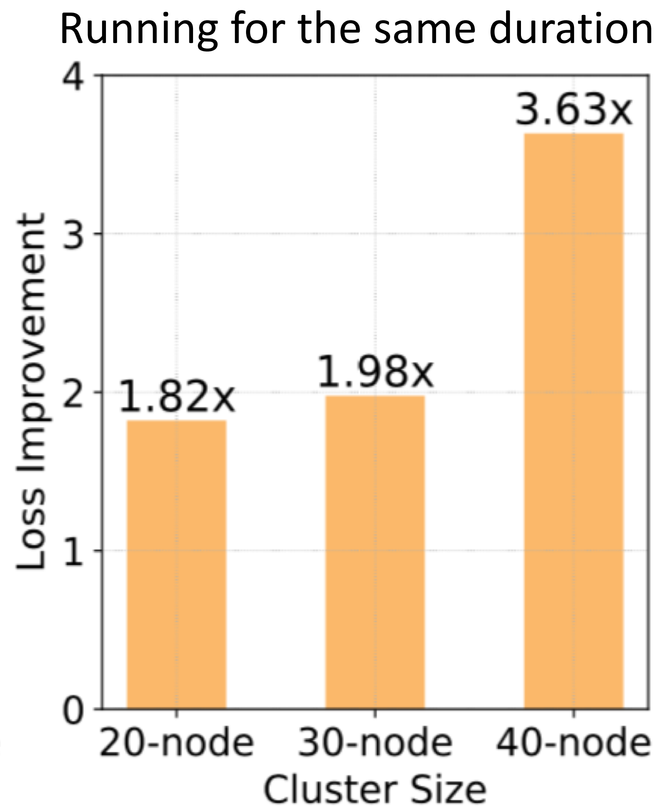
- Heterogeneity increases inconsistency, affects performance
- SpecSync work both in homogeneous and heterogeneous settings

Robustness

- Scalability

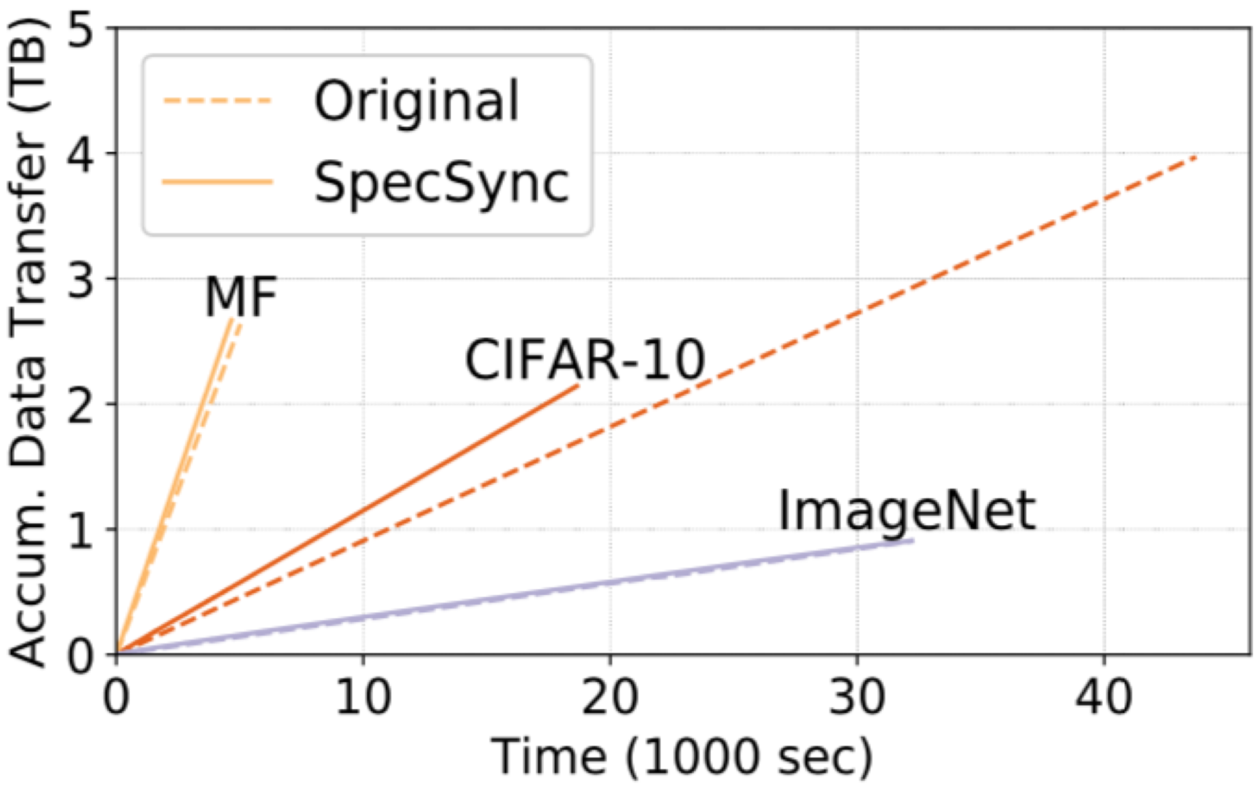
20, 30, 40 m4.xlarge





Communication Overhead

SpecSync introduces additional communication



- The accumulated communication does not increase

Conclusion

- Investigated inconsistency in distributed ML
- Proposed SpecSync to actively improve freshness
- Designed an adaptive hyperparameter tuning algorithm
- Implemented SpecSync atop MXNet and evaluated it.

Thank you for listening!

Q&A